Integration of Marine CSEM and Seismic AVA Data for Reservoir Parameter Estimation

G. Michael Hoversten, Jinsong Chen, Erika Gasperikova, Gregory A. Newman*
Lawrence Berkeley National Laboratory

Summary

Reservoir fluid saturations and porosity are estimated using a two-stage process consisting of an uncoupled geophysical inversion of marine seismic amplitude versus angle (AVA) and controlled source electromagnetic data, followed by a Bayesian inversion, using the geophysical parameters derived in the first stage and a rock-physics model to estimate reservoir parameters. The two-stage process has the advantage that it can be done using existing industry software, with only the addition of the electromagnetic inversions to estimate electrical conductivity. The estimated water saturation and porosity compare well to both log data and those derived from a formal joint inversion of marine AVA and electromagnetic data. However, the two-stage estimates of oil and gas saturation do not compare favorably to those obtained using a formal joint inversion of both data sets simultaneously.

Introduction

Recent developments in the application of controlled source marine electromagnetic (CSEM) data in petroleum exploration have brought this technology to the attention of many in exploration and production within the oil and gas industry. These developments are founded on more than two decades of research carried out in academia and at U.S. national laboratories. The commercial availability of CSEM data now makes it possible to consider integrating this new data with existing seismic data in ways that will add considerable value. In particular, the sensitivity of CSEM data to water saturation (S_w), when combined with the spatial and reservoir parameter sensitivity (porosity, S_w, gas saturation [S_g], and oil saturation [S_o]) of seismic data, can provide enhanced prediction of fluid saturations within existing or prospective reservoirs.

There are many ways in which CSEM and seismic data can be combined to estimate reservoir parameters. The possibilities range from what we term cooperative inversion, in which both data sets are used without any formal linkage in the inversion of either, to fully coupled joint inversion, in which both data sets are inverted simultaneously to directly estimate reservoir parameters. Hoversten et al. (2003) present an example of the former, in which crosswell EM and seismic travel-time tomography are used to estimate reservoir parameters using time-lapse changes in shear velocity, electrical conductivity, and acoustic velocity to sequentially strip off the effects of pressure and water saturation before estimating oil and CO_2 saturations. Direct reservoir parameter estimation by joint inversion was demonstrated by Hoversten et al. (2004), where marine CSEM and AVA data were used in a formal joint inverse to estimate reservoir S_w, S_o, S_g, and porosity (ϕ). The formal joint inversion is currently being extended to replace the 1D CSEM solution with full 3D. While the development and testing of more computationally demanding approaches is underway there is interest in an approach that can be deployed quickly.

One method for combining seismic and CSEM data is a relatively straightforward extension of what is currently done using seismic data alone (Bachrach and Dutta, 2004). The use of Bayesian inversion, which couples a rock-physics model with estimates of geophysical parameters, can be extended to include electrical conductivity. In this paper, we demonstrate the use of AVA inversion to estimate acoustic- (V_p), shear-velocity (V_s), and density (ρ) coupled with 3D CSEM (Newman and Boggs, 2004) inversion to estimate electrical conductivity (σ) in a Bayesian inverse for reservoir fluid saturations and ϕ. This approach is compared to the formal joint inversion described by Hoversten et al. (2004, 2005).

Theory and Method

There are three components to the integration of seismic and CSEM data for reservoir parameter estimation using the two-stage approach mentioned above. These are:

1) Inversion of the data sets to produce estimates of geophysical parameters (V_p, V_s, ρ, and σ).
2) Development of a rock-physics model that links geophysical parameters to reservoir parameters.
3) Application of Bayesian inversion, which takes the estimated geophysical parameters (along with prior information) and combines the estimated geophysical parameters with predicted geophysical parameters from the rock-physics model in the likelihood function, to estimate the reservoir parameters.

Geophysical Inversion

Seismic V_p, V_s, and ρ are estimated in a depth window covering the reservoir, using a Gauss-Newton type inversion of AVA data. The Zoeppritz equation is used to calculate the angle dependent reflectivity, which are convolved with angle dependent wavelets to form the calculated seismic data. The inversion is formulated as a least-squares minimization in which the functional (θ), given by (1), is minimized. *F[m]* is the forward model operator, *m* and m_{ref} are the model and reference model parameter vectors respectively.

$$\theta = 1/2\left\{\left(F[m]-d^{obs}\right)\right\}^T D^{-1}\left\{\left(F[m]-d^{obs}\right)\right\} + \lambda/2\left\|W(m-m_{ref})\right\|^2 \quad (1)$$

The observed data (d^{obs}) are amplitude-versus-angle (AVA) gathers that have had NMO and residual NMO applied in addition to removal of multiples. NMO stretch at the far offsets as well as any internal mode conversions are neglected. Linearizing (1) about a given model, m^i, at the i^{th} iteration produces the quadratic form;

$$\left[DJ^T DJ + \lambda W^T W + \alpha C^T C\right] m_{i+1} = DJ^T DJm_i + DJ^T D\delta d_i + \alpha C^T h \quad (2)$$

where m_{i+1} is solved by using a quadratic programming algorithm that allows bounding of the parameters. D is a data weighting matrix (usually a diagonal of the inverse of observed errors), W is a regularization matrix (usually representing the first spatial derivatives of the model parameters) and the current difference between calculated (d_i) and observed data (d_{obs}) is given by $\delta d_i = d_{obs} - d_i + J_i m_i$, where J is the Jacobian matrix, or sensitivity matrix. The Lagrange multiplier λ is adjusted from large to small as iterations proceed. Additional linear relations such as a velocity-density relationship are implemented using a separate Lagrange multiplier, α.

The electrical conductivity is estimated by 3D CSEM inversion using the algorithm described by Newman & Boggs (2004).

Rock-Physics Model

The estimation of reservoir parameters requires a rock-properties model that links the reservoir with geophysical parameters. The model we have adopted uses the Hertz-Mindlin contact theory for the dry-frame bulk and shear moduli of a dense, random pack of spherical grains. Modified Hashin-Shtrikman lower bounds are used to calculate the effective moduli for porosities below the critical porosity. This model is used in a combined seismic and EM inversion described by Hoversten et al. (2003). Archie's law is used to model electrical resistivity as a function of ϕ and S_w. The fluid bulk moduli and densities of brine, oil, and gas, respectively, are computed using relations from Batzle and Wang (1992).

The field data come from the Troll Field in the North Sea. Log data from a well approximately 4 km to the northeast of the geophysical survey was used to derive the rock-physics model. Seismic rock-physics model parameters are found by using a simplex algorithm to minimize L_1, given by Equation (3).

$$L_1 = \sum_1^N \left|V_p^{obs} - V_p^{calc}\right| + \sum_1^N \left|\rho^{obs} - \rho^{calc}\right|, \quad (3)$$

where $V_p^{obs}, V_p^{calc}, \rho^{obs}, and\, \rho^{calc}$ are the sonic log compressional velocity, model-calculated compressional velocity, log density, and model calculated density, respectively.

We have found that the estimated grain shear modulus, grain density, and Poisson's ratio are nearly equal to that of feldspar (the dominate grain type in the reservoir) if the logged V_p is first reduced by 5%. The size of the reduction in V_p (5%) is chosen from modeling of the frequency dependent velocity in porous media (Muller and Gurevich, 2004).

The three parameters, C, m, and n, of Archie's law, Equation (4), are found by linear regression in the log10 domain:

$$R_{bulk} = CS_w^{-m}\phi^{-n} \quad (4)$$

Employing the S_w, R_{bulk}, and ϕ logs from the same well used for the seismic model parameters yields values of 0.78 Ωm, 1.31 and 0.14 for C, m, and n, respectively. The low value of n indicates very little sensitivity to porosity. This was also noted in developing Archie's law parameters for logs from the Snorre field in the North Sea (Hoversten et al., 2001) and was caused, in that case, by clay filling the pore space. The small value of n causes the CSEM inversions to be relatively insensitive to ϕ.

Bayesian Inversion

We use a Bayesian model (Chen et al. 2004) to estimate reservoir parameters at each pixel in space, which include ϕ, S_w, S_g, S_o = 1-(S_g+S_w), and pore pressure, given the inverted, co-located bulk modulus (k_b), shear modulus (k_s), density (ρ), and natural logarithmic of electrical conductivity (σ). Based on Bayes theorem, the joint posterior distribution of unknown variables at each pixel in space is given by the following formula:

$$f(\phi, S_w, S_g, P \mid k_b, k_s, \rho, \sigma) \propto f(k_b, k_s, \rho, \sigma \mid \phi, S_w, S_g, P) f(\phi, S_w, S_g, P). \quad (5)$$

The first term on the right side of Equation 5 is referred to as the likelihood function, which is the connection between the input data and unknown variables. The second term is referred to as the prior distribution function, which is a summary of all the information not included in the data. Equation 5 is correct up to an unknown normalizing constant, which is not needed for Markov chain Monte Carlo (MCMC) methods employed here.

We use a MCMC sampling method similar to the ones presented in Chen and Hoversten (2003) to obtain many samples of each unknown variable from the joint posterior distribution function. The method includes three major steps: (1) deriving full conditional distribution function for each variable; (2) sequentially drawing samples from those conditional distributions; (3) making inferences from those samples. Details of the sampling methods used can be found in Gilks et al. (1996).

Examples

Seismic and marine CSEM data were acquired over a portion of the Troll Field in 2003. Twenty four CSEM receiver units were laid out in a line, with a nominal separation of 750 m. A 220 m electric dipole transmitter, producing an 800 amp square wave, was towed at 2 knots along the receiver line in both directions, producing data at the receivers for transmitters on either side of the receiver. The electric dipole transmitter is nominally aligned with the survey line, with course corrections and ocean currents producing some variation in the orientation of the transmitter along the line. Received CSEM data along with the transmitter locations and current are recorded as time series. In postprocessing, the CSEM time series are averaged to produce in-phase and out-of-phase electric fields for average transmitter locations spaced 100 m apart along the line. The transmitter fundamental is 0.25 Hz. There is sufficient power to extract the third and fifth harmonics, so that three frequencies (0.25, 0.75, and 1.25 Hz) were acquired.

A 3D seismic data set was also acquired in 2003 and processed to produce NMO corrected gathers suitable for AVA inversion. Figure 1 shows the estimated V_p and ρ from AVA inversion in the upper two panels (V_s was also estimated but is not shown). The CSEM data from all 24 receiver stations on the line were inverted simultaneously, using the 3D finite-difference based inversion code described by Newman & Boggs (2004). The resulting conductivity section is shown in the lower panel of Figure 1.

The geophysical data shown in Figure 1 (along with estimate V_s) were used as input data to the Bayesian inversion. Figure 2 shows the estimated S_w (upper panel), ϕ (middle panel), and S_g (lower panel).

Considerable well control exists in the area of the survey line. The current interpretation based on geophysical and production data is that the reservoir unit (outlined by black dots in Figures 1 and 2) is predominantly gas and oil filled in the upper two-thirds of the section shown to the left of the fault at approximately -4,500 m. To the left of this fault (on the down thrown side) the reservoir unit is brine filled. The two-stage estimates show a zone of relatively high S_g on the down thrown side of the fault where only brine is expected. Modeling and analysis continues to assess these results in light of the existing interpretation.

Figure 3 shows a comparison of the fluid saturation estimates and ϕ at the well location made by full joint inversion (Hoversten et al., 2004) and the two-stage approach described here. Both types of inversion produce good agreement with logged values for S_w and ϕ. However, the two-stage process has done a poor job of estimating S_o and S_g.

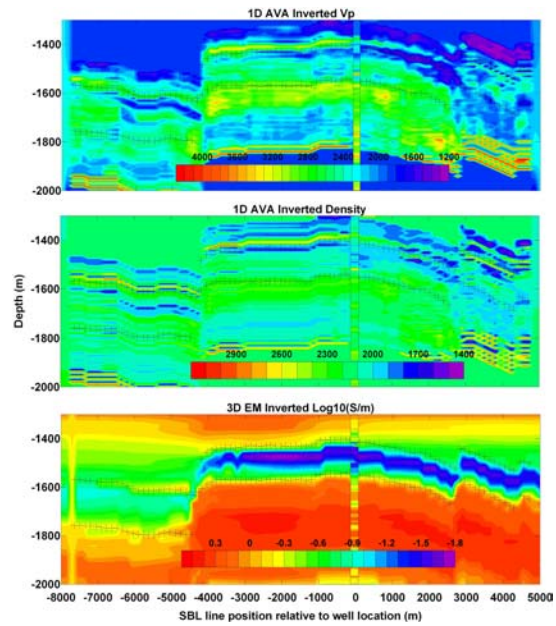

Figure 1: Inverted V_p (upper panel), ρ (middle) and σ (lower) used for Bayesian inversion for reservoir parameters. Black plus symbols outline the reservoir interval. Log values are overlaid at the well location for comparison.

Conclusions

A two-stage process of inversion for geophysical parameters followed by Bayesian inversion is an attractive alternative to full joint inversion of seismic and CSEM data sets, because two-thirds of the pieces already exist within the normal industry work flow. Only electromagnetic inversion has to be added to estimate electrical conductivity. The tests conducted here show that this simple-to-implement two-stage process provides good estimates of S_w and ϕ, but poor estimates of the oil and gas saturations.

Work continues on evaluating the affect of prior information and errors in the geophysical parameter estimates required in the Bayesian process. Improvements in estimated S_o and S_g from the two-stage process are possible.

References

Bachrach, R**.,** and N. Dutta, 2004, Joint estimation of porosity and saturation and effective stress and saturation for 3D and 4D seismic reservoir characterization using stochastic rock physics modeling and Bayesian inversion. 74th Ann. Internat. Mtg.: Soc. of Expl. Geophys., SEG Expanded Abstracts **23**, 1515–1518.

Batzel, M., and Wang, Z., 1992, Seismic properties of pore fluids, Geophysics., **57**, 1396-1408.

Chen, J., and Hoversten, M., 2003, Joint stochastic inversion of geophysical data for reservoir parameter estimation. 73rd Ann. Internat. Mtg.: Soc. of Expl. Geophys., SEG Expanded Abstracts **22,** 726-729.

Chen, J., Hoversten, G.M., Vasco, D. W., Rubin, Y., Hou, Z., 2004, Joint inversion of seismic AVO and EM data for gas saturation estimation used a sampling based stochastic model. 74th Ann. Internat. Mtg.: Soc. of Expl. Geophys., SEG Expanded Abstracts **23,** 236-239.

Hoversten, G.M., Cassassuce, F., Gasperikova, E., Newman, G. A., Chen, J., Rubin, Y., Hou, Z., and Vasco, D., 2005, Direct reservoir parameter estimation using joint inversion of seismic AVO & marine CSEM data, Geophysics, (In review).

Hoversten, G.M., Cassassuce, F., Newman, G.A., 2004, Direct reservoir parameter estimation using joint inversion of seismic AVO & marine CSEM data. 74th Ann. Internat. Mtg.: Soc. of Expl. Geophys., SEG Expanded Abstracts **23**, 1507-1510.

Hoversten, G.M., Gritto, R., Washbourne, J., Daley, T., M., 2003, Pressure and Fluid Saturation Prediction in a Multicomponent Reservoir, using Combined Seismic and Electromagnetic Imaging, Geophysics, **68**, 1580-1591.

Hoversten, G.M., Newman, G.A., Morrison, H.F., Gasperikova, E., and Berg, J.I., 2001, Reservoir characterization using crosswell EM inversion: A feasibility study for the Snorre Field, North Sea: Geophysics, **66**, 1177-1189.

Muller, T., and Gurevich, B., 2004, Attenuation and dispersion of seismic waves in 3-D randomly inhomogeneous, porous rocks: Extended abstract for the EAGE Conference, Paris, 7-10 June 2004, Paper number H033

Newman G.A. and Boggs, P.T., 2004, Solution accelerators for large-scale three-dimensional electromagnetic inverse problems, Inverse Problems, **20**, S151-S170.

Acknowledgments

Support for this work was provided by the Assistant Secretary for Fossil Energy, through the National Energy Technology Laboratory, under U.S. Department of Energy under Contract No. DE-AC03-76SF00098. We are grateful to Statoil for supplying the CSEM data over Troll and to EMGS and Shell for their contributions of data and consultations. In particular, we thank Tage Rosten of Statoil, Jaap Mondt and Maren Kleemeyer of Shell and Rune Mittet of EMGS. In addition, we thank the Troll partners (Norsk Hydro, Statoil, Petoro, Norske Shell, Total, and ConocoPhillips) for permission to publish this work.

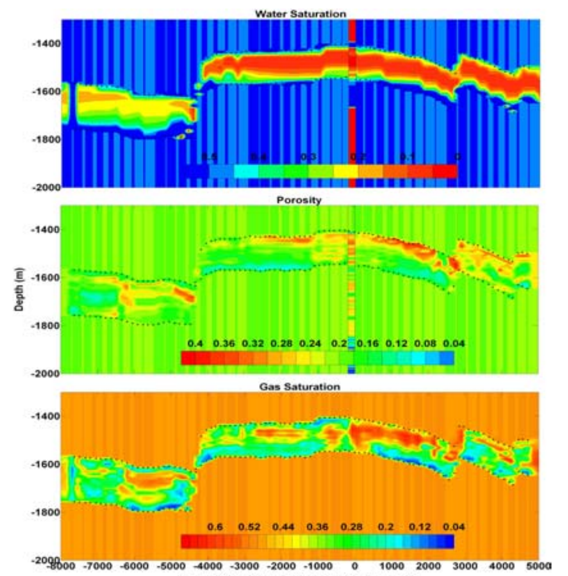

Figure 2: Estimated S_w (upper panel), ϕ (middle panel) and S_g (lower panel) from Bayesian inversion of the geophysical parameters shown in Figure 1. Log values are at the well location for comparrison. Estimates shown only in the reservoir.

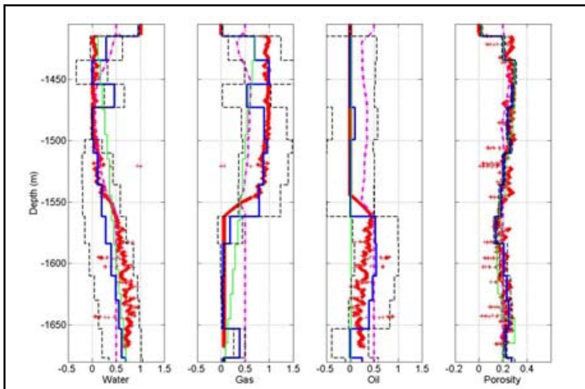

Figure 3: Comparison of estimated reservoir parameters using full joint inversion and using the two-stage inversion process. Panels from left to right are S_w, S_g, S_o and, ϕ. Full joint inversion estimates are shown by the blue line, red dots are log values, dashed black lines are 95% confidence estimates on joint inversion estimates, and dashed magenta lines are estimates from Bayesian inversion in the two-stage process.

EDITED REFERENCES

Note: This reference list is a copy-edited version of the reference list submitted by the author. Reference lists for the 2005 SEG Technical Program Expanded Abstracts have been copy edited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

Integration of Marine CSEM and Seismic AVA Data for Reservoir Parameter Estimation

REFERENCES

Bachrach, R**.,** and N. Dutta, 2004, Joint estimation of porosity and saturation and effective stress and saturation for 3D and 4D seismic reservoir characterization using stochastic rock physics modeling and Bayesian inversion: 74th Annual International Meeting, SEG, Expanded Abstracts, 1515–1518.

Batzel, M., and Z. Wang, 1992, Seismic properties of pore fluids: Geophysics, **57**, 1396-1408.

Chen, J., and M. Hoversten, 2003, Joint stochastic inversion of geophysical data for reservoir parameter estimation, 73rd Annual International Meeting, SEG, Expanded Abstracts, 726-729.

Chen, J., G. M. Hoversten, D. W. Vasco, Y. Rubin, and Z. Hou, 2004, Joint inversion of seismic AVO and EM data for gas saturation estimation used a sampling based stochastic model: 74th Annual International Meeting, SEG, Expanded Abstracts, 236-239.

Hoversten, G. M., F. Cassassuce, E. Gasperikova, G. A. Newman, J. Chen, Y. Rubin, Z. Hou, and D. Vasco, 2005, Direct reservoir parameter estimation using joint inversion of seismic AVO & marine CSEM data: Geophysics (In review).

Hoversten, G. M., F. Cassassuce, G. A. Newman, 2004, Direct reservoir parameter estimation using joint inversion of seismic AVO and marine CSEM data: 74th Annual International Meeting, SEG, Expanded Abstracts, 1507-1510.

Hoversten, G. M., R. Gritto, J. Washbourne, T. M. Daley, 2003, Pressure and fluid saturation prediction in a multicomponent reservoir, using combined seismic and electromagnetic imaging: Geophysics, **68**, 1580-1591.

Hoversten, G. M., G. A. Newman, H. F. Morrison, E. Gasperikova, and J. I. Berg, 2001, Reservoir characterization using crosswell EM inversion: A feasibility study for the Snorre Field, North Sea: Geophysics, **66**, 1177-1189.

Muller, T., and B. Gurevich, 2004, Attenuation and dispersion of seismic waves in 3-D randomly inhomogeneous, porous rocks: 66th Annual Conference, EAGE, Extended Abstracts, H033.

Newman, G. A., and P. T. Boggs, 2004, Solution accelerators for large-scale three-dimensional electromagnetic inverse problems, Inverse Problems, **20**, S151-S170.